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Output Gap Estimation for Inflation Forecasting: The Case of the Philippines

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Inflation Forecasting:
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Series No. 2007-01

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Center for Monetary and Financial Policy
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ABSTRACT

This paper examines alternative estimation models for obtaining output gap measures for the Philippines. These measures are combined with the rates of growth of broad money, nominal wages and oil prices for forecasting inflation. We find that models which combine these leading indicators in a nonlinear way outperform other linear combinations of these variables for out-of-sample forecasting performance.

Key words: forecasting, output gaps, principal components

JEL Classification: E5, F4

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Output Gap Estimation for Inflation Forecasting: The Case of the Philippines

Paul D. McNelis* and Cristeta B. Bagsic†

August 2007

It is better to read the weather forecast before we pray for rain.

— Mark Twain

[M]easurement error has important effects for the appropriate conduct of the monetary authority as well as for policy performance. In most circumstances, an authority that takes explicit account of the uncertainty in the environment in which it operates is more successful than an authority that turns a blind eye to the issue.

— Orphanides, et al (2000)

1 Introduction

The output gap is an argument for the interest rate, along with current inflation and lagged interest rates, in most discussions of Taylor rules for central banks. The rationale is that a positive output gap is an indicator of inflationary pressure not seen in actual inflation. Yet, there is considerable uncertainty over the output gap and its key component, potential output. Does a rise or fall in current GDP mean a change in potential output or just a cyclical change in demand? These alternatives have different policy implications. Central banks can raise interest rates to curb a rise in demand but cannot affect potential output.

In this paper we examine three measures for obtaining potential output – and thus the output gap – for the Philippine economy. These measures are the Hodrick-Prescott (HP) filter, the constant elasticity of substitution (CES) production function, and the structural vector

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autoregressive (SVAR) approaches for obtaining measures of the output gap. We find that all three measures help forecast inflation. We argue that the BSP should adopt a “thick model” approach to output gap estimation for inflation forecasting, making use of all of these measures as well as information from the rates of growth of broad money, nominal wages, and the price of oil.

To put the main purpose of our paper in perspective, we first take a look at the role of the inflation forecasting process within the policy-setting framework at the Bangko Sentral ng Pilipinas. In Section 3 is a brief survey of theoretical and empirical issues concerning the role of output gap estimates in the inflation targeting (IT) regime, and the results of an informal survey we conducted among selected central banks that estimate the output gap. Section 4 presents our alternative measures of the output gap. We turn to models of inflation, both for in-sample understanding and for out-of-sample forecasting in Section 5. Section 6 concludes.

2 The Forecasting Process at the BSP

The inflation targeting (IT) framework is implemented in the Philippines by announcing the inflation target two years ahead. For instance, the annual target of 4 percent for 2008 was announced in December 2006.¹ As a consequence, policy discussions in the BSP are generally focused on monthly forecasts two years forward of the inflation rate, as well as on the developments and outlook for economic variables that help predict inflation on the one hand, and decision variables on the other.

Throughout the policy-setting process, the synergy between seasoned judgment of both the modelers and decision makers, and the quantitative tools is apparent. The models, in particular, both shape and are refined by consultations and discussions at various levels. To arrive at the inflation targets and the inflation forecasts, the BSP typically follows the process shown in Figure 1.²

The forecasting process follows the decision making cycle for monetary policy. Policy meetings are held at an interval of six weeks. Before each meeting, the Technical Staff prepares a policy decision support paper for submission to the Advisory Committee, an internal body composed of senior officials tasked to submit recommendations on monetary policy to the Monetary Board. The Advisory Committee discusses the contents of the policy paper, which reviews recent developments concerning conditions pertaining to, among other things, aggregate demand, supply-side conditions, the labor market, domestic liquidity, financial markets,

¹ Starting December 2006, the inflation target announced is the midpoint of a two-percentage-point spread. Previously, targets were in the form of a one-percentage-point-thick range. See BSP Media Release of 14 December 2006 for details on the shift.

² The BSP is instrument independent but is goal dependent. Thus, in setting the inflation targets, the illustrated internal process in Figure 1 is supplemented by coordination with the National Government through the Development Budget Coordination Committee (DBCC) - where the BSP sits as an observer - of the National Economic and Development Authority (NEDA) Board. This coordination ensures that the inflation targets do not only enjoy ownership and institutional support of the fiscal authorities, but more importantly it ensures the consistency and coherence in the assumptions used in economic planning, target-setting and forecasting done by the different agencies.

and the global economy. The Committee also discusses the outlook for inflation, starting with the latest forecasts prepared by Bank staff along with the emerging risks to future inflation and other information relevant to the policy stance. On the basis of its view of the inflation outlook and prevailing economic conditions, the Advisory Committee formulates a policy recommendation to the Monetary Board. If necessary, the forecasts are revised to reflect important new information that becomes available prior to the policy meeting of the Monetary Board later in the same week.

At the policy meeting of the Monetary Board, the Deputy Governor for monetary policy presents to Monetary Board the information contained in the policy paper, which incorporates the comments as well as the recommendations of the Advisory Committee. The Monetary Board then makes its decision on the stance of monetary policy on the basis of the inflation forecasts and its assessment of the balance of risks to inflation as well as other information made available during the discussion.

2.1 The Forecasting Models

The BSP currently uses two forecasting models: its Multi-Equation Model (MEM) and its Single Equation Model (SEM). The MEM has eight (8) behavioral equations and four (4) identities. Meanwhile, the SEM has inflation rate in its left-hand side; and financial depth measured by M4/nominal GDP, the national government's cash position, 91-day Treasury bill rate, domestic oil price, nominal wage, non-oil import prices and a dummy for the rice crisis in 1995 as explanatory variables. Both of these models give monthly forecasts of the CPI inflation rate.

Aside from being the richer model, the MEM captures output gap, albeit in a limited way. The deviation of agricultural production from trend is one of the explanatory variables in the inflation equation in the MEM.³

Table 1 shows the forecasting performance of the models of the BSP in the last five (5) years. The mean absolute error (MAE) is the 12-month average of the monthly absolute errors for one-month ahead forecasts. The absolute error is computed as the difference in percentage points between the absolute value of actual inflation and the forecast of inflation for month t conditional on information available in month $t - 1$.

In effect, over the last five (5) years, the BSP's monthly one-period ahead forecasts are on average 0.156 - 0.342 percentage points away from actual inflation. The covariance proportions cited in Table 1 indicate that the remaining forecasting errors of both models are more than 98 percent unsystematic. More importantly, the Theil inequality coefficient is very close to zero.

The MEM's structure and forecasting performance, meanwhile, has made it the default workhorse for policy simulations at the BSP. BSP analysts have primarily used the MEM for quantitative predictions of the lagged effects of policy actions on inflationary developments

³Refer to BSP's First Quarter 2007 Inflation Report, which is available in its website www.bsp.gov.ph, for the evaluation of the impact of including the output gaps we estimate here in its MEM. In general, our estimated output gaps improved the MEM's forecasting power.

	Mean Absolute Error (one-month ahead forecasts)	
	Single-Equation Model	Multi-Equation Model
2002	0.342	0.296
2003	0.156	0.290
2004	0.271	0.222
2005	0.309	0.247
2006	0.176	0.264
Theil Inequality Coefficient	0.0008 (1988-2006)	0.0008 (1985-2006)
<i>Bias Proportion</i>	<i>0.0000</i>	<i>0.0008</i>
<i>Variance Proportion</i>	<i>0.0022</i>	<i>0.0131</i>
<i>Covariance Proportion</i>	<i>0.9978</i>	<i>0.9861</i>

Source: Department of Economic Research-Bangko Sentral ng Pilipinas

Table 1: Forecasting Performance Evaluation

and, in turn, on the real economy and BSP's decision variables. Nevertheless, and in recognition of these various and variable lags and of current advances in research and computing technologies, research and modeling resources have lately been employed to enhance the forecasting power of BSP's other model – the annual Long Term Macro Model (LTMM) – and to develop new ones that can better explain the transmission channels of policy actions to the real economy.

The BSP's research agenda and institutional plans reflect a strategy for enhancing modeling capacity over the next five (5) years. The accuracy and performance of the current crop of models are assessed on an on-going basis. More importantly, models are updated or developed at the instance of either the Board, senior management, or the technical staff. Starting in late 2005, forecasting, and model updating and development have been assigned to two different units in order to give equal emphasis to both activities. The extensive job of making periodic forecasts of economic and financial variables has been given to the newly-created Economic and Financial Forecasting Group (EFFG). On the other hand, the tasks of updating current models and developing new ones (like the current subject model for output gap estimation) have been assigned to the, also newly-created, Center for Monetary and Financial Policy (Center from hereon).

3 Use of Output Gap Among Central Banks

Monetary policy affects real and nominal variables through a number of channels: the direct exchange rate channel to CPI inflation; the real-interest rate channel to aggregate demand (AD); the credit channel to aggregate demand to inflation; the wealth channel to aggregate

demand to inflation; and the exchange rate channel to aggregate demand to inflation.

The transmission channels to AD are also the channels to the output gap. Higher AD will increase the output gap, which can then lead to an increase in inflation as higher production increases the costs of production, and higher demand allows firms to increase prices. In the long term, monetary policy can, at best, provide a stable environment for the real economy. Bad and volatile monetary policy generates a macroeconomic environment that discourages investment and, therefore, growth in potential output.

As Taylor (2000) has pointed out, the “output gap is a key variable in most policy rules, but it is important whether or not a central bank follows a policy rule”. (p.17) The value of an output gap measure to a central bank is in the signal it may provide about developments in future inflation.

Output gap is typically defined as the percent difference between actual output and potential output. Potential output is the output that the economy can produce at full employment. It is also seen as the level of output that is compatible with a stable rate of inflation. A positive output gap indicates inflation pressure not seen in actual inflation. However, because potential output is unobserved, different estimation models can give divergent estimates of output gaps for a given economy.

It cannot be overemphasized that output gap estimation is not without a lot of uncertainties. According to Orphanides, et al (2003), the “most problematic element associated with real-time estimates of the output gap is that it is based on end-of-sample estimates of an output trend (potential output), which are unavoidably highly imprecise”. Current period estimates of the output gaps generally are based on forecasts of current period actual and potential GDP. Once the data on GDP (and the other variables used to estimate potential output) become available in the following quarter, they may still be preliminary for sometime and quite likely to be revised. At the same time, updating the model for one more data point once the statistics for the following period become available could also affect the trend. Another possible source of measurement error is the model used, as when the central bank uses a model it believes give the true gap when in fact it does not.

The accuracy of output gap estimates acquires added importance to a monetary authority which explicitly includes output gap in its loss function. Even so, Taylor (2000) finds that despite the difficulty associated with output gap estimation, monetary authorities must respond to it. “Pre-emptive strikes – such as that taken in the United States in the late 1980s and not taken (at least [not] soon enough or large enough) in Japan in the late 1980s – require that the central bank begin to raise interest rates when the output gap increased [...] even though there may not be a noticeable movement in inflation.” (p.17)

McCallum (2001) warned monetary authorities against “respond[ing] strongly” to these estimates of the gap given the uncertainty that the estimation approach used give an accurate estimate of the output gap. Smets (1998) showed that as the uncertainty in output gap estimates increases, the efficient policy response in a framework such as the Taylor rule would be to lower the weight or the feedback parameter of the output gap. He added that “when

measurement error in the output gap becomes large, the efficient Taylor rule parameter on the output gap could fall to zero.” He clarified, however, that “uncertainty in the output gap does not affect optimal central bank behaviour in a linear-quadratic framework [even as] it can have significant effects on restricted instrument rules such as the Taylor rule.” (p.15)

While it is true that accurate estimates of current period output gap is of immense interest to policymakers, forecasts of future-period output gaps also provide additional insights. Simulating expected paths of output gap given various policy action options would help clarify the decision-making process. Therefore, resolving the typical end-sample problem, exhibited by univariate filters for instance, though necessary, will not be sufficient to address fully the policy dilemma.

3.1 The Taylor Curve

The Taylor curve describes a negative relationship between inflation rate volatility and output growth volatility where output volatility is in the y-axis and inflation rate volatility is in the x-axis.⁴ Strict inflation targeting implies an aggressive and volatile policy stance leading to considerable volatility in interest rates and the exchange rate that will then result to higher volatility of output. Flexible inflation targeting has price stability in the form of an inflation target as its primary goal; but gives some consideration to stabilizing output movements around potential output. This means allowing a longer time horizon to achieving the inflation target than what is technically doable.

Should an inflation targeting central bank also attempt to stabilize output? More categorical still, does output stabilization enhance an IT framework? Debelle (1999) succinctly illustrated the role of output stabilization in an inflation-targeting policy environment. He illustrated the objective function of an IT central bank using the following simple model which consists of the Phillips curve, an aggregate demand function, and the central bank’s loss function, respectively, as follows:

$$\pi_t = \pi_{t-1} + \alpha (y_{t-1} - y_{t-1}^*) + \varepsilon_t \quad (1)$$

$$y_t = y_t^* + \beta (y_{t-1} - y_{t-1}^*) - \gamma (r_{t-1} - r^*) + \eta_t \quad (2)$$

$$L_t = E_t \sum_{s=t}^{\infty} \delta^{s-t} \left[(1 - \lambda) (\pi_s - \pi^*)^2 + \lambda (y_s - y_s^*)^2 \right] \quad (3)$$

Adopting Debelle’s (1999) notations, π is inflation, π^* is the inflation target, y is output, y^* is potential output, r is the short-term real policy rate, δ is a discount rate, and ε_t and η_t are independent and identically distributed shocks, and r^* is the neutral real interest rate.

⁴See Taylor (1979).

Note that two-period ago short-term real interest rate affects one-period ago output, which in turn affects current period inflation rate. Economists have pointed to this difference in lag structure as the basis of the tradeoff.

The above model solves r , thus:

$$r_t = r^* + \varphi_1 (\pi_t - \pi^*) + \varphi_2 (y_t - y_t^*) \quad (4)$$

The output gap is thus incorporated in a Taylor-type reaction function (Equation 4), which could be used in either a positive or a normative manner.

Previous studies have concluded that IT is enhanced by keeping in check output volatility. Assuming that monetary policy affects the real economy in the short run, strict inflation targeting leads to changes in interest rates and, in effect, the foreign exchange as often as the number of times that inflation deviates from target.⁵ Strict inflation targeting requires that deviations of actual inflation from target be eliminated at a minimum period and without regard to impact on growth. This implies volatile interest rates, foreign exchange, and output. The induced volatility in interest rates and foreign exchange could eventually translate to instrument instability. On the other hand, wild fluctuations in output performance are inimical to welfare maximization. In any case, even when a central bank chooses to be a strict inflation targeter – formally, it is when the deviation of actual output from potential has zero weight in its objective function – the output gap still has information content because it portends inflation expectations. However, to be relevant to monetary policy decision makers, estimates must go beyond that of the historical series. For example, the estimates of the current gap and expected output gap given alternative policy actions would be useful.

In the same vein Svensson (2002) found that flexible IT provides the greatest benefit compared to strict inflation targeting and strict output targeting. A target horizon of one to two years is one of the imprints of a flexible IT regime.⁶

Nonetheless, Debelle (1999) cites that even for strict inflation targeters (where the central bank's loss function gives zero weight to deviation of output from potential), output gap is useful. Output gap signals inflation expectations. Put simply, a positive output gap portends inflationary pressure (i.e., either rising inflation rate or accelerating inflation rate).

3.2 Central Bank Practices

Using Philippine data, Yap (2003) concludes that the output gap has a role to play in the Philippine IT framework. He observes that including the output gap variable in an inflation model (a two-step error correction model, with Dubai crude oil, exchange rate and money supply on the right hand side) for the Philippines improves its performance, e.g., higher adjusted R^2 . He uses three measures of output gap: a time trend model, an unobserved component method, and the H-P filter.

⁵For instance, see Svensson (2002).

⁶The Philippines follows a 2-year target horizon.

	Estimation Methodology	Estimation Frequency	Publication Frequency
Reserve Bank of Australia	Production Function Multi-variate HP filter	Quarterly (since mid 90s)	Not regularly.
People's Bank of China	Production Function State-space estimation	Quarterly (2001)	Internal use.
Hong Kong Monetary Authority	Production Function	Quarterly (2001)	Internal use.
Bank Indonesia	SVAR	Quarterly (1999)	Internal use.
Bank of Japan	Production Function	Quarterly (2003)	2x/year
Bank Negara Malaysia	Production Function Multi-variate HP filter	Quarterly (1998)	annual
Reserve Bank of New Zealand	Multi-variate HP filter	Quarterly	Not regularly.
Monetary Authority of Singapore	Multi-variate HP filter HP filter Variable Span Smoother	Quarterly	Not regularly.

Table 2: Survey of Use of Output Gaps Among Members of the Executives' Meeting of East Asia-Pacific Central Banks (EMEAP) Group

Inflation targeting central banks that use output gaps include, among others: the Bank of England, Bank of Canada (BoC), Reserve Bank of New Zealand (RBNZ), Reserve Bank of Australia (RBA), Bank Indonesia, Bank of Norway, and the Sveriges Riksbank.

The Reserve Bank of New Zealand estimates output gap using a multivariate filter, which, in the case of New Zealand, is a Hodrick-Prescott (H-P) filter augmented with residuals from a Phillips curve relationship and two Okun's law equations (unemployment gap and capacity utilization gap). The output gap has been a considerable factor in RBNZ's structural macro-model. (Graff, 2004)

The Bank of Canada, meanwhile, has used a structural vector autoregression approach and extended multivariate filter to estimate output gap. (Rennison, 2003) It incorporates an output gap variable in the reaction function embedded in its Quarterly Path Model. (Longworth and Freedman, 2000)

On the other hand, the Riksbank publishes three output gap measures in its Inflation Report: the H-P filter (with smoothing parameter of 6400), an unobserved component measure using an Okun's Law and Phillips curve relationships to extract the cyclical component of output from inflation and unemployment, and a production function model which uses capital stock and employment data to estimate potential output. The output gap is used to assess inflationary expectations. (Sveriges Riksbank, 2005)

In the case of Indonesia, Bank Indonesia's general equilibrium model incorporates a Taylor-like reaction function in which policy rates respond to inflation and the output gap. (Joseph, et al, 2003)

Table 2 shows the results of an informal survey conducted by the BSP on members of the Executives' Meeting of East Asia-Pacific Central Banks (EMEAP) group. Among the respondents, the production function approach to estimating output gap is the most prevalent, followed by the use of the multivariate Hodrick-Prescott filter. Quarterly estimation is favored. Lastly, none of the eight (8) respondents have made output gap an official statistic.

4 Output Gap Measures

Prevalent theory assumes that output gap accounts for a portion of the transitory or cyclical portion of real output. Viewed another way, output gap is that component of actual output arising from demand shocks. The output gap is, likewise, deemed as the portion of real output that is associated with unanticipated inflation.

According to Orphanides, et al (1999), the "difficulties [in measuring potential output] spring from a certain fundamental ambiguity in the concept of potential aggregate output. [...] the economy's productive potential is typically defined as the trend component of actual output, with trend estimated in various ways. Alternatively, potential output is inferred from the behavior of inflation". (p.4)

In general, the data determine the appropriate output gap measure. Broadly speaking, the methodologies used in the estimation of potential output may be classified into two: statistical detrending techniques, and methodologies that link potential output with other economic variables as dictated by economic theory. Statistical detrending techniques decompose a time series into permanent and cyclical components. Examples of these techniques are: Hodrick-Prescott (H-P) filter, Beveridge-Nelson decomposition, and various unobserved components methods. On the other hand, the structural VAR, production function, and multivariate system models use economic theory to separate the impacts of structural and cyclical components of output. Examples of output gap measures which decompose the output into its trend and cycle components are:⁷

1. linear trend method: ordinary least squares (OLS), with linear deterministic trend
2. quadratic trend method: OLS, with quadratic deterministic trend
3. breaking linear trend model: OLS, incorporates structural breaks/slowdowns
4. Hodrick-Prescott model: based on the filter proposed by Hodrick and Prescott in 1997 with their recommended smoothing parameter of 1600 for quarterly data
5. band-pass filter method
6. Beveridge-Nelson method: models output as an ARIMA(p,1,Q) series
7. unobserved components model:
 - (a) univariate models:

⁷Measures 1-8 and their descriptions are quoted from Appendix A of Orphanides and van Norden (2004).

- i. Watson method: models the output trend as a random walk with drift and the cyclical component as a stationary AR(2) process
 - ii. Harvey-Clark model: follows the Watson method but does away with the assumption of a constant drift in the trend component
 - iii. Harvey-Jaeger method: has the same trend component as the Harvey-Clark model but assumes a cyclical component that is a stochastic process
- (b) multivariate models
 - i. Kuttner model: adds a Phillips curve to the Watson method
 - ii. Gerlach-Smets method: adds a Phillips curve to the Harvey-Clark model
- 8. Blanchard and Quah's structural vector autoregression (SVAR) model: imposes long-run restriction on output to a VAR system. One obvious advantage of SVAR measure, in general, is that they do not suffer end-of-sample problems. They are also able to forecast expected output gaps.
- 9. Cochrane method: a two-variable VAR that estimates the permanent and cyclical components of output. This approach exploits the permanent-income hypothesis, and is founded on the assumptions that (i) consumption and GNP are cointegrated, and (ii) consumption follows a random walk process.
- 10. Production function approach: generally implemented by calculating potential output given the trends in employment and capital.

For this exercise we used the HP filter, CES production function, and SVAR to estimate the output gap for the Philippines. We discuss our three alternative measures and show quantitative estimates for the output gap below.

4.1 HP Filter

This method is between and betwixt detrending and first differencing of data. The advantage is that it is easy and quick to use. The following equation describes the filter:

$$\text{Min} \left\{ \sum_{t=0}^x (y_t - y_t^x) + \omega \sum_{t=0}^x [(y_{t+1}^x - y_t^x) - (y_t^x - y_{t-1}^x)]^2 \right\} \quad (5)$$

The parameter ω is the controlling parameter for the smoothness of the trend. It is usually set at 1600. The output gap is defined simply as $y_t - y_t^x$, the difference between actual log output less the smoothed trend output. This is clearly a mechanical device which defines cycles it extracts by the choice of the smoothing parameter ω .

Despite ease of use, which contributes to its widespread acceptance, care should be given in evaluating its resulting output gap. For one, the choice of ω is arbitrary. For another, it is sensitive to new or additional observations. The optimization problem the HP filter solves has two components: deviation from trend, and smoothness of trend. A significant positive deviation from trend necessitates lifting the trend prior to and lowering the trend after the

shock. In other words, it is penalized for changing the trend. However, at the end of the sample, this disincentive is absent.

Actual and potential output appear in Figure 2.

4.2 CES Production Function

The Constant Elasticity of Substitution production function was originally developed by Arrow, Chenery, Minhas and Solow (1961) as an alternative to the more familiar Cobb-Douglas production function. It has the following functional form:

$$Y_t = A \cdot Z_t [(1 - \alpha)L_t^{-\kappa} + \alpha K_t^{-\kappa}]^{-\frac{1}{\kappa}} \quad (6)$$

The variable Z_t is the aggregate total factor productivity shock, A is a constant term, while α , $(1 - \alpha)$ represent the coefficients for capital K and labor L , known as distribution parameters which explain the relative factor shares in total output. The parameter κ is the substitution parameter.

The CES production yields the following equations for the marginal products of labor and capital:

$$\frac{\partial Y_t}{\partial L_t} = A^{1-\kappa} Z_t^{1-\kappa} (1 - \alpha) \left(\frac{Y_t}{L_t} \right)^{\kappa+1} \quad (7)$$

$$\frac{\partial Y_t}{\partial K_t} = A^{1-\kappa} Z_t^{1-\kappa} \alpha \left(\frac{Y_t}{K_t} \right)^{\kappa+1} \quad (8)$$

The elasticity of substitution of capital and labor, symbolized by $\eta_{K,L}$, is given by:

$$\eta_{K,L} = \frac{1}{1 + \kappa} \quad (9)$$

A necessary condition for a unique steady-state is that $\kappa \leq 0$. This CES function reduces to the Cobb-Douglas log-linear function under the assumption that $\kappa = 0$.

Using a second-order Taylor expansion of equation (6) with the dependent variable re-defined as $y_t = Y_t/L_t$, with $k_t = K_t/L_t$, and assuming Constant Returns to Scale, the CES function takes the following form:

$$\log(y_t) = \log(A) + \lambda \cdot tr + \alpha \log(k_t) - .5\kappa\alpha(1 - \alpha) [\log(k_t)]^2 + \epsilon_t \quad (10)$$

The parameter λ picks up a trend term.

The main advantage of the CES is that it uses production theory, based on capital, labor, and trend terms. It is not, like the H-P filter, an ad-hoc mechanical application to one data

series. On the other hand, the production function model suffers from the fact that the series needed to estimate it, especially in emerging economies, are generally of poor quality or even unavailable.

We define the output gap as the residual between $\log(y_t)$ and $\widehat{\log(y_t)}$, or simply $\hat{\epsilon}_t$. This is not the normal practice. If measures of capacity utilization and full-employment were available, we could use the estimated production function to generate potential output under assumptions of full capacity utilization and non-accelerating inflation full employment. In this case, actual utilized labor and estimates of the capital stock are available; however, structural unemployment rate is not available. The capital utilization rate is available only for the manufacturing sector starting late 1990s.

Table 3 gives the estimates for the CES production function coefficients for equation (10). Only the time trend, λ , is statistically significant. Nonetheless, the parameter κ is close to zero and negative, implying a unique steady-state and an elasticity of substitution between capital and labor of greater than unity.

Actual and potential output estimates are plotted in Figure 3.

Nonlinear Estimates		
Parameter	Pt. Estimate	Robust St. Dev.
A	1.76	290.53
λ	0.0045	0.0018
α	0.387	124.82
κ	-0.0001	147.96

Table 3: CES Production Function

4.3 SVAR Approach

The structural vector autoregression (SVAR) method uses a wider set of variables, not just output, capital, labor, and trend terms. It is based on a vector autoregressive model of the form:

$$[I - A(L)]Y_t = u_t \quad (11)$$

where $A(L)$ is a lag operator, Y a matrix of endogenous variables, and u a matrix of residuals. Equation (11) is known as the Reduced Form (*RF*) Model. The idea behind this approach is to convert the multivariate *AR* given by equation (11) into a restricted Wold moving average (*MA*) process:

$$\begin{aligned} Y_t &= [I - A(L)]^{-1}u_t \\ &= S(L)\varepsilon_t \end{aligned}$$

We impose linear restrictions relating the innovations of the MA process ε_t to the residuals of the reduced form estimated VAR model at time t , u_t , for a k -variable model:

$$\begin{aligned}\varepsilon_t &= S(0)u_t \\ E(\varepsilon_t, \varepsilon_t') &= S(0)E(u_t u_t')S'(0) = \Sigma.\end{aligned}$$

The basic point of SVAR estimation is simple and straightforward. Knowledge of $S(0)$, the matrix of contemporaneous effects of the structural disturbances ε_t on Y_t allows us to recover the structural shocks from the reduced-form residuals u_t . In estimating the SVAR, we first estimate a Bayesian VAR model. The logarithm of output enters in first-differences and is the first variable in the model.

Thus, changes in potential output Δgdp^p and the output gap Δgdp^g can be written as:

$$\Delta gdp^p = S_{11}(0)\varepsilon_{1,t} + S_{11}^*(L)\varepsilon_{1,t} \quad (12)$$

$$\Delta gdp^g = S_{12}(L)\varepsilon_{2,t} + \dots + S_{1k}(L)\varepsilon_{k,t} \quad (13)$$

The model tells us that the permanent component of changes in actual GDP is simply its own current and lagged innovations or shocks. This represents the non-cyclical, permanent innovations to real GDP coming from purely exogenous technological change or other sources beyond the control of policy. The cyclical component of the change in GDP is explained by the lagged (not current) values of other variables in the model.

It is important to note that potential GDP and the GDP gap are presented as first differences, not in terms of levels. We can convert these into levels by starting from an initial estimate of $\log(gdp)$. The calculation of the output gap is within the structure of the VAR/SVAR model. We do not compare actual output with a trend level or level of output from a production function. We simply compare the output generated by permanent shocks to GDP with the level of output generated by cyclical or demand-side variables within the VAR framework. It is conceptually different from the HP and CES measures.

In the SVAR estimation, we use the following seasonally adjusted variables: the logarithmic change in real GDP, Δy , the logarithms of the real exchange rate and employment, given by RER , and L ; the rate of interest, $WAIR$; and the deficit/GDP ratio, given by $DEFGDP$.

Table 4 gives the point estimates for the SVAR estimation. We see that $DEFGDP$ is positively affected by innovations in Δy . Meanwhile, $WAIR$ has a negative relationship to the contemporaneous shocks to δy , and positive relationship with $DEFGDP$. According to our model, a positive shock to Δy will tend to depreciate the RER during the same period, while RER has a positive relationship with innovations to $DEFGDP$ and $WAIR$. Positive shocks to Δy and $DEFGDP$ have a negative effect on L during the same period. On the other hand, L is positively related to shocks to $WAIR$ and RER . Table 4 gives the standard errors of the point estimates.

The cyclical and permanent components of output from the SVAR estimation appear in Figure 4.

Contemporaneous Arguments: Point Estimates:					
Dependent Variable	Δy	DEFGDP	WAIR	RER	L
Δy	1.000				
DEF/GDP	0.153	1.000			
WAIR	-0.003	0.114	1.000		
RER	-1.146	1.042	0.009	1.000	
L	-0.640	-0.176	0.003	0.100	1.000
Unrestricted Contemporaneous Arguments: Std Errors					
Dependent Variable	Δy	DEF/GDP	WAIR	RER	L
Δy					
DEFGDP	0.023				
WAIR	3.239	0.021			
RER	0.084	0.054	0.0004		
L	0.044	0.028	0.0002	0.008	

Table 4: Point and Standard Errors of Impulse Responses

4.4 Comparing Gap Estimates

Figure 5 presents all three gap measures. These are the gap measures for the full sample. We see that the SVAR measure is considerably more volatile than the HP and CES measures.

The dip in the early 1990s seen in the output gaps estimated using Equations (5) and (6) reflects the power crisis that saw widespread power outages in the Philippines during the period. Its resolution and the subsequent market reforms coincided with the rise in the output gaps from these measures. The period of the Asian crisis and the subsequent El Niño episode show declining HP and CES output gaps once again. In contrast, the SVAR output gap declined much earlier and spiked as the other two measures bottomed. Interestingly, the SVAR results during this period are consistent with the rising inflation rate.

More recently, even as all three measures show positive gaps for estimation done until Q3 2006, they are also all starting to turn southwards.

5 Inflation Forecasts

The proof of the pudding is in the eating: how well do these alternative measures help forecast inflationary developments? We do not know what exactly the “output gap” is, so why not use all three? We find that all three are helpful for recursive out of sample forecasts. For in-sample forecasts, the HP and CES are significant but the SVAR measure is not. But the best overall model for forecasting is one which uses information from all three measures as explanatory variables.

The benchmark model against which we compare the explanatory power of models with various output gap measures and other leading indicators, is a model with only the own lags

of inflation. We then explore alternative models: (1) lags of inflation and HP gap; (2) lags of inflation and CES gap; (3) lags of inflation and SVAR gap.

We also make use of additional leading indicators: the annualized rates of growth of broad money $\Delta_4 m3_t = (m3_t - m3_{t-4})$, nominal wages $\Delta_4 w_t = (w_t - w_{t-4})$, and the price of oil $\Delta_4 po_t = (po_t - po_{t-4})$.

Additionally, we used linear and non-linear principal components to “distill” one measure from all three, and used these alternatives. In all of our model, we define inflation as $p_t - p_{t-4}$.

5.1 Alternative Models: Distilling Information from Indicators

Stock and Watson (2000) have shown that the best way to forecast inflation is to combine information from a wide class of potential leading indicators or explanatory variables. We have six possible indicators: the three output gap measures, as well as the rates of growth of broad money, wages and the price of oil.

One way to combine the information from these variables is to make use of principal component methods.

Linear principal components for a set of variables is equivalent to a series of orthogonal regressions. Given a data set X consisting of T observations for H variables, we find the first principal component by computing the eigenvalues and eigenvectors from the following equation:

$$[X'X - \nu_i I] \mathbf{V}_i = 0$$

where ν_i is the i -th eigenvalue and \mathbf{V}_i is the associated eigenvector of dimension $(H \text{ by } 1)$ for eigenvalue ν_i . For linear principal components, the first linear principal component is simply the matrix X multiplied by the eigenvector associated with the first or largest eigenvalue, \mathbf{V}_1 :

$$PC_1 = X \cdot \mathbf{V}_1$$

For a matrix of rank H , there can be at most H eigenvalues. Figure 6 illustrates the setup of linear principal components. The variables $x1$ through $x4$ map into each other through the H -unit set of principal components.

An alternative to linear principal components is the use of nonlinear auto-associative maps. Just as in linear principal components, the variables $x1$ through $x4$ map into each other. Figure 7 shows one example of a nonlinear principal component. The variables $x1, \dots, x4$ map into each other, as before, but they do so through a set of encoding receptors, usually logistic functions, represented by the boxes $c11$ and $c12$, onto at most $H - \text{units}$, where $H = 4$. The $H - \text{units}$ are then decoded by the logistic functions in boxes $c21$ and $c22$.

Alternative Forecasting Models for Inflation		
Model	Arguments	
Reference	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	
1	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$ygap_{HP,t-1} \dots ygap_{HP,t-k}$
2	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$ygap_{CES,t-1} \dots ygap_{CES,t-k}$
3	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$ygap_{SVAR,t-1} \dots ygap_{SVAR,t-k}$
4	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$\Delta_4 m3_{t-1} \dots \Delta_4 m3_{t-k}$
5	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$\Delta_4 w_{t-1} \dots \Delta_4 w_{t-k}$
6	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$\Delta_4 po_{t-1} \dots \Delta_4 po_{t-k}$
7	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$LPC_{t-1} \dots LPC_{t-k}$
8	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$NPC_{t-1} \dots NPC_{t-k}$
9	$\Delta_4 p_{t-1} \dots \Delta_4 p_{t-k}$	$TM_{t-1} \dots TM_{t-k}$
Note: LPC: linear principal component of gap/growth variables NLP: non-linear principal component of gap/growth variables TM: trimmed mean of gap, growth, LPC, NPC variables		

Table 5: Alternative Forecasting Models

We combine the three output gaps and the three growth rates for a nonlinear principal component to see if this provides additional information not gleaned by the linear principal component.

Finally, using all the information from the three output gaps, the three growth rates, the linear and nonlinear principal components, we construct a trimmed mean (the mean cutting out the highest and lowest 10% outliers), to form a single leading indicator that we use in Model 9.

We summarize the models we use in Table 5.

5.2 In-Sample Performance

Before evaluating the forecasting performance, we first examine the performance of the model on the full data set. The results appear in Table 6. We should note that the data we use in the in-sample estimation differ from the data used in forecasting. In forecasting arguments, the output gaps are recursively updated. We do not use the full-sample output gaps as arguments for forecasting inflation in earlier periods of the model.

We see that model 5, with lagged wage growth arguments, is statistically significant at the ten percent level. We chose a lag length of six for inflation and wage growth to ensure that the residuals were free of autocorrelation.

	Reference	1	2	3	4	5	6	7	8	9
RSQ	0.921	0.927	0.924	0.925	0.930	0.937	0.933	0.924	0.925	0.928
Granger Tests of Causality										
Model										
		1	2	3	4	5	6	7	8	9
p-values		0.593	0.898	0.806	0.386	0.070	0.190	0.882	0.836	0.512

Table 6: In-Sample Forecasts Evaluation

	Reference	1	2	3	4	5	6	7	8	9
RMSQ	0.022	0.021	0.023	0.023	0.023	0.023	0.025	0.021	0.02	0.0243
% GAIN		5.91	-3.64	-4.55	-4.55	-3.18	-14.09	3.18	8.18	-10.45
DM-Significance Test for Prediction Accuracy: Model 8 vs. Reference										
Lags for correction for autocorrelation										
	1	2	3	4	5	6	7	8		
dmstat	1.29	1.189	1.314	1.63	2.348	2.79	2.003	1.561		
p-value	0.099	0.117	0.095	0.052	0.009	0.003	0.023	0.059		
Clark and West Test for Predictive Accuracy with Nested Models										
Lags for correction of variance/covariance matrix										
	1	2	3	4	5	6	7	8		
clarkwstat	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016		
p-value	0	0	0	0	0	0	0	0		

Table 7: Out-of-Sample Forecasts Evaluation

5.3 Out-of-Sample Performance

Table 7 gives the out-of-sample forecasting performance of the models. We see that the best model, in terms of overall forecasting performance, is model 8, with the nonlinear principal component of the three output gap measures as well as wage, broad money, and oil price growth rates. The forecasting improvement over the benchmark model is 8.2 percent. This performance is statistically significant, based on the Diebold-Mariano (dmstat) and Clark-West (clarkwstat) tests of comparative forecasting accuracy. The statistic dmstat tells us whether the improvement in accuracy is statistically significant, while clarkwstat tells us whether the additional variable in Model 8 is just a noise variable. The p-values show that the improvement in accuracy is statistically significant and that the variable *NPC* is not just a noise variable.

6 Concluding Remarks

The uncertainties in output gap estimation arise from model selection and data issues. For example, statistical issues such as data quality and data revisions have been known to contradict prior appreciation of output gap estimates. It is in this context that the Philippine monetary authorities will find the use of a “thick model” attractive, if not a necessity during periods when indicators of inflation do not all point in one direction.

This study does not make any determination on how much weight the central bank should accord the output gap in setting the policy stance. The determination of such weight, as well as exercises to measure the degree of uncertainty arising from data revision and model selection, and to remedy data weaknesses, is a subject for future research.⁸

Given the significant relationship between Philippine inflation rate and the output gap, efforts to better understand and improve estimates of the output gap should serve the BSP well. We conclude, in the spirit of Sargent, Williams and Zha (2004) that it is important to acknowledge model uncertainty about the formation of output gap measures in the formulation of monetary policy, and make use of thick models, or combinations of models.

⁸In a comment to the authors, BSP Monetary Board Member Vicente B. Valdepeñas Jr. noted that, “the problem of uncertainties in output gap estimates [...] requires measurement. Once the degree of uncertainty has been identified and measured, say, by Monte Carlo method, this derived information could be used to adjust estimates of the output gap. This will not in itself eliminate the uncertainty in the source data. However, once measured and identified, one becomes aware of the extent to which the uncertainty intrudes into the estimation process. One can use Bayesian Monte Carlo techniques to determine the PDF of this uncertainty. It is not a complete remedy. However, one has the comfort that the uncertainty has been factored into the output gap estimation, and that its impact is statistically defined.”

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Appendix

A Data

A.1 Constructed data

Labor

To estimate the full-time equivalent employment level, L , quarterly data on mean hours worked per sector, and the number of employed who reported for work per sector are used. It is assumed that one who is employed full-time works for 40 hours per week.

Procedure in Calculating L_t

1. Get the sum of the number of employed who reported for work for sector i , $EW_{i,t}$.

$$EW_{i,t} = \sum EW_{i,t}^{hrs} \quad (14)$$

where $EW_{i,t}^{hrs}$ denotes the number of employees in sector i who worked for one of the following *hrs* categories: <20 hours, 20-29 hours, 30-39 hours, and ≥ 40 hours.

2. Calculate the weight for each sector, $w_{i,t}$, by dividing the actual mean hours of sector i , $mean_{i,t}$ by 40 hours.

$$w_{i,t} = \frac{mean_{i,t}}{40} \quad (15)$$

3. Calculate the full-time equivalent employment level for each sector.

$$L_{i,t} = EW_{i,t} \times w_{i,t} \quad (16)$$

4. L_t is the sum of $L_{i,t}$ across all i 's.

Capital

In calculating the capital stock for the quarter, $CAPITAL_t$, we need to assume an initial capital stock, and a depreciation rate. The end-1984 $CAPITAL$ in the database of BSP's LTMM is the chosen starting capital stock. This is an arbitrary choice.

1. Depreciate previous quarter's capital stock, $CAPITAL_{t-1}$, by the assumed aggregate depreciation rate of 5 percent.

$$CAPITAL_{t,begin} = (1 - deprate) \times CAPITAL_{t-1} \quad (17)$$

$$= (0.95) \times CAPITAL_{t-1} \quad (18)$$

where *deprate* is the depreciation rate.

2. Get the current period's increase in capital stock. From the *Expenditure-Side* table of the NIA,

$$I_t = FCF_t - CS_t - OD_t \quad (19)$$

where I_t is the flow of capital for the current period, FCF_t is *Fixed Capital Formation*, CS_t is *Changes in Stocks*, and OD_t is *Orchard Development*.

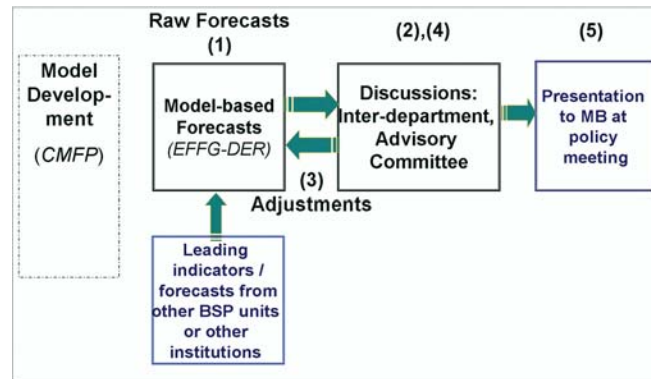
3. The capital stock is, therefore,

$$CAPITAL_t = [(0.95) \times CAPITAL_{t-1}] + I_t \quad (20)$$

A.2 Data Used in SVAR Estimation

1. *GDP* levels and *L* levels are deseasonalized in *Eviews* using either *TRAMO-SEATS* or *X11-ARIMA*. The other variables are not deseasonalized.
2. *DEFGDP* is the ratio of national government fiscal deficit to nominal GDP for the same period.
3. *WAIR* is the quarterly weighted average of 91-day Treasury bill rates sourced from the BSP's *DBank*.
4. *RER* used is the real effective exchange rate calculated using a basket of major trading partners's currencies. It is taken from the *DBank*.
5. *L* is the same as the constructed full-time-equivalent labor, *L*, above.

B Figures



Note: **CMFP** refers to the Center for Monetary and Financial Policy, **EFFG-DER** refers to the Economic and Financial Forecasting Group of the Department of Economic Research and **MB** refers to the Monetary Board.

Figure 1: The Forecasting Process at the BSP

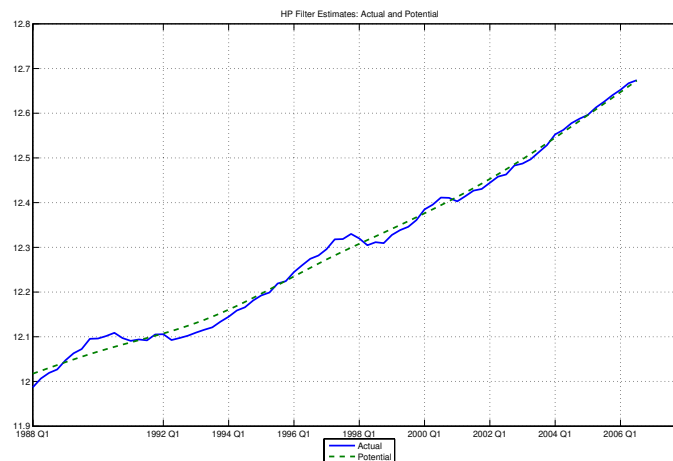


Figure 2: Hodrick-Prescott Filter: Actual and Potential Output

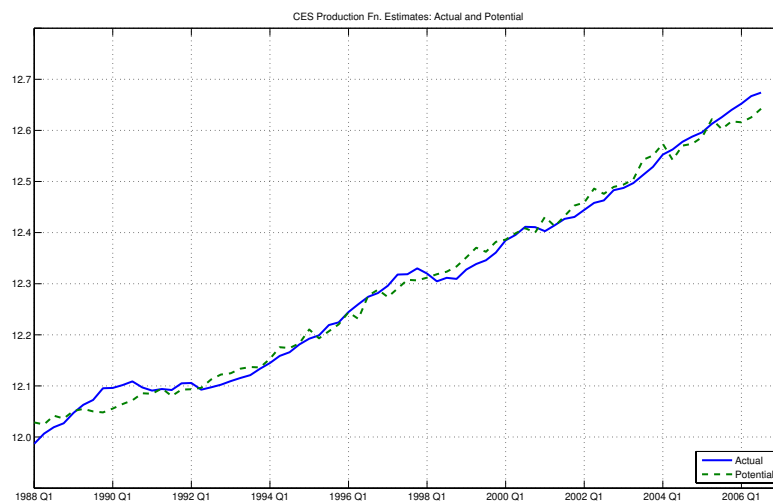


Figure 3: CES Production Function Estimates: Actual and Potential Output

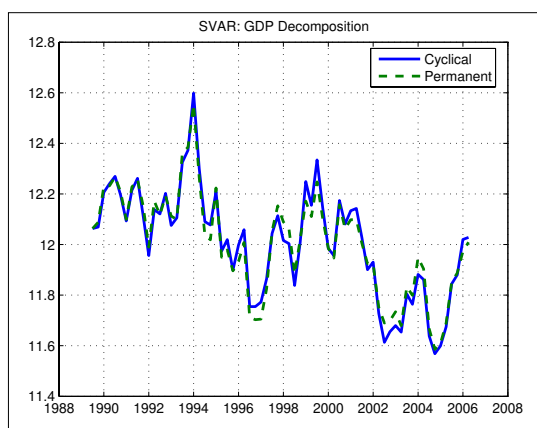


Figure 4: Structural Vector Autoregression (SVAR) Output Decomposition

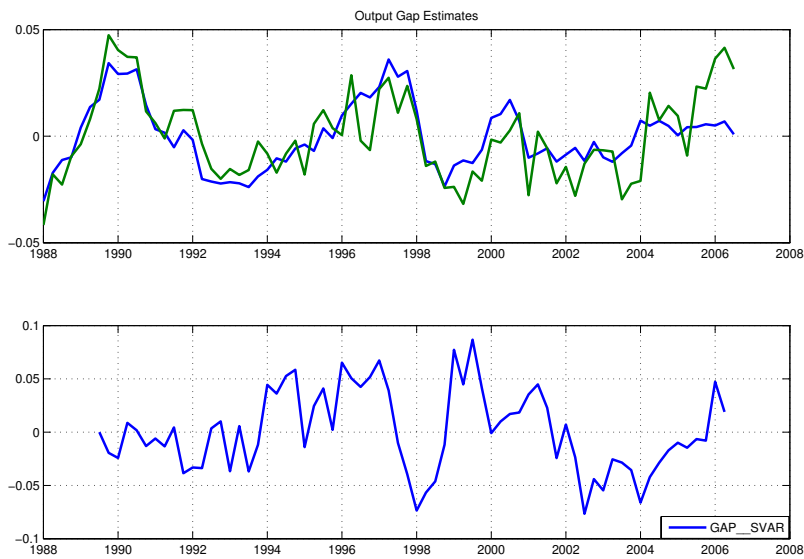


Figure 5: Output Gap Estimates Using HP Filter, CES Production Function, and SVAR

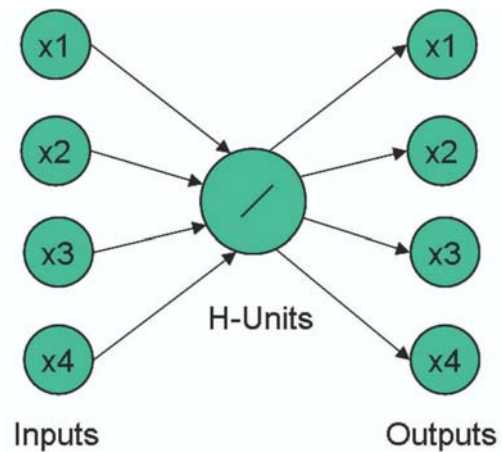


Figure 6: Linear Principal Components

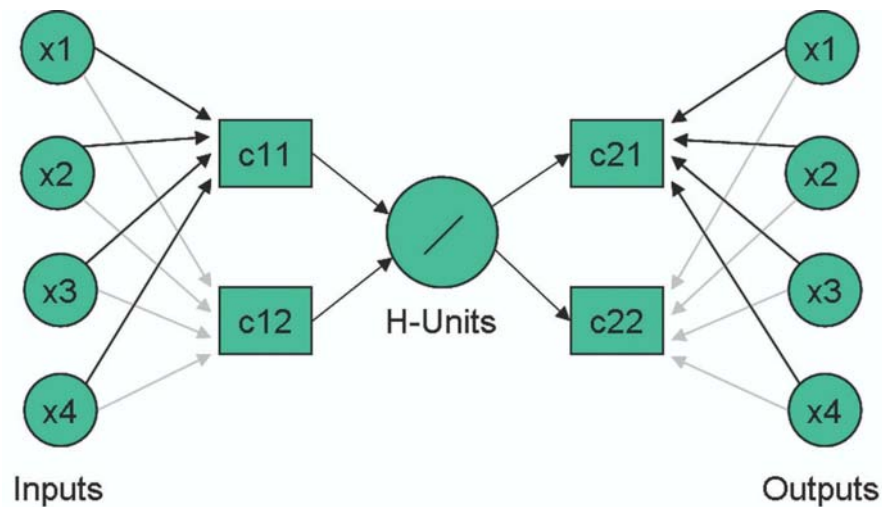


Figure 7: Nonlinear Principal Components

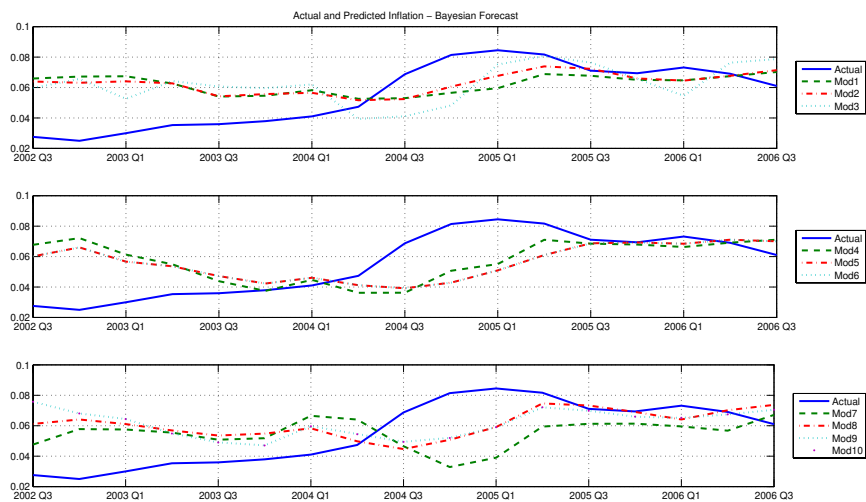


Figure 8: Inflation and Inflation Forecasts: Upper and Lower Bounds

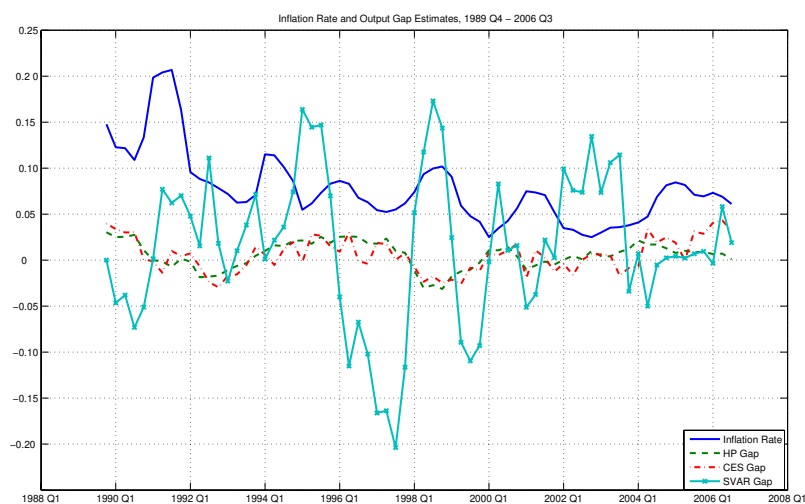


Figure 9: Inflation Rate and Output Gap Estimates: 1989 Q4 - 2006 Q3